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Research Article

Website-Based Boycott Product Detection System using Convolutional Neural Network: A comparison of YOLOv8 and VGG16

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Abstract:
Introduction: Product boycotts have become a common form of social response in the digital era, yet manual identification of boycotted products can be slow and inaccurate. This study develops a website-based system and compares YOLOv8 and VGG16 for automated identification of boycott and non-boycott products from images. **Method**: A dataset of 4,250 food and beverage product images, comprising 3,638 boycott and 612 non-boycott products, was collected from internet sources and divided into 70% training, 20% validation, and 10% testing sets. YOLOv8 was trained using 640×640-pixel inputs as a one-stage object detector, while VGG16 used 224×224-pixel inputs with transfer learning as an image classifier. Both models were integrated into a website-based detection system and evaluated using accuracy, precision, recall, and F1-score. **Results and Discussion**: On 425 test images, YOLOv8 achieved 91.7% accuracy, 99.7% precision, 90.3% recall, and a 94.9% F1-score, substantially outperforming VGG16, which achieved 51.3% accuracy, 81.6% precision, 55.7% recall, and a 66.2% F1-score. YOLOv8 demonstrated greater robustness to variations in background, lighting, and product appearance because of its object-localization capability. **Conclusion**: YOLOv8 is more effective than VGG16 for website-based boycott product detection and provides a stronger foundation for practical real-time identification systems.

Keywords: Boycott Product Detection, Convolutional Neural Network, YOLOv8, VGG16, Image Classification.

1. Introduction

The rapid development of information technology has had a significant impact on various aspects of human life, including social awareness and public response to global issues [1], [2]. Social media now plays a crucial role in shaping public opinion and economic decisions [3]. One form of public reaction to social and political issues that is increasingly common in the digital age is boycotting certain products [4]. Product boycotts are usually used as a form of protest against corporate or state policies that are considered contrary to moral, social, or humanitarian values [5]. In practice, people often spread information about boycotted products through social media or other online information channels [6]. However, the dissemination of such information is still manual, unsystematic, and often not accompanied by accurate supporting data, making it difficult for people to know whether a product is boycotted or not [1], [5].

Based on these issues, a technological solution is needed to help the public identify boycott products more quickly and accurately. One approach that can be used to solve this problem is to utilize artificial intelligence technology, specifically the Convolutional Neural Network (CNN) method, which is a machine learning method that has been proven effective in classifying and detecting objects in digital images. With this capability, CNN can be used to develop an image-based boycott product detection system that can be accessed through a website platform. In this study, two Convolutional Neural Network (CNN) architectures were used, namely YOLOv8 and VGG16, each of which has its own characteristics and advantages in performing visual classification.

Previous studies have highlighted the importance of systems that can help people quickly and accurately identify boycott products. Fitriani et al. (2025) emphasize that product boycotts, especially those supporting humanitarian issues such as the Palestinian cause, are widely discussed and monitored through social media, requiring an integrated system to make it easier for people to make purchasing decisions that align with their values [7]. Ltifi (2020) shows that product boycotts in crisis situations have a major impact on brand image and consumer perceptions of the product, making the development of an information system capable of monitoring, detecting, and providing up-to-date data on boycotted products very important [8].

Based on these issues, this study focuses on answering two main research questions. First, can single-stage detectors (such as YOLOv8) outperform standard image classifiers (such as VGG16) in recognizing boycott products on the same dataset? Second, how do the two architectures differ in terms of precision and recall, and what are the implications for everyday public use?

This study aims to overcome the problem of manual identification by developing a website-based boycott product detection system using the Convolutional Neural Network (CNN) method. The main contribution of this study is the provision of a fully functional website system and transparent live trials so that the public can identify boycott products efficiently and accurately simply by uploading product images [9].

2. Method

This study uses an experimental approach with systematic stages to develop and test a website-based boycott product detection system using the Convolutional Neural Network (CNN) method. The initial steps taken are data collection, dataset, data split, data preprocessing, algorithm application, evaluation, and application testing. Details of the method stages can be seen in **Figure 1**.

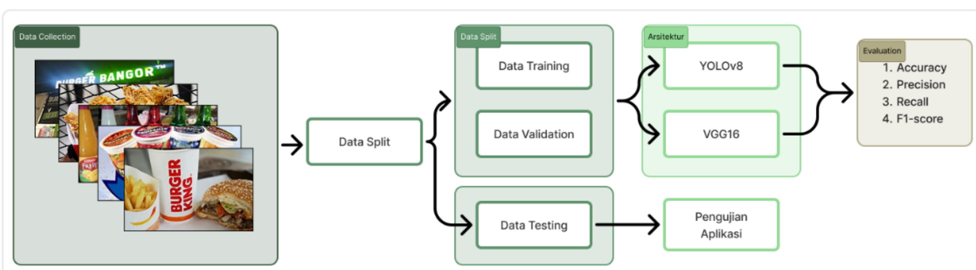

Figure 1. Research Framework

Data Collection

The dataset was collected through web scraping and manual downloading from the internet, focusing on food and beverage products included in the public boycott list as well as non-boycotted alternative products circulating in the local market [10]. All images used in this study were collected from public sources for non-commercial academic purposes under the principle of Fair Use. The complete dataset is openly available to support transparency and replication of the study at the following link: https://url-shortener.me/28W1.

Data Preprocessing

A dataset is a collection of data used as the basis for training, testing, and evaluating models in a study. The dataset used in this study consists of 4,250 images, covering a wide variety of products. To apply the YOLOv8 algorithm, the entire dataset was used without explicit class division because this architecture has an internal classification mechanism based on direct object detection. Meanwhile, for the VGG16 algorithm, the data was classified into two main classes, namely 3,638 images of boycott products and 612 images of non-boycott products. To prevent data leakage, the data division process was carried out before the resizing operation. The data was divided into three parts, namely 70% for training, 20% for validation, and 10% for testing. The image input size was also automatically adjusted according to the architecture requirements, namely 640x640 pixels for YOLOv8 and 224x224 pixels for VGG16. The system only focused on image-based detection and did not include text-based identification or other descriptions. Details of the dataset can be seen in **Table 1**.

Table 1. Dataset Details

Kategori	Number of Samples	Product	Number of Samples
Boycot	3.638	Foods	2.261
		Drinks	1.377
Non-boycot	612	Foods	200
		Drinks	412

The implementation and testing of the system were carried out using computer hardware (laptop) with 8 GB of RAM and supported by a stable internet connection. Software development was carried out using the Python programming language. The main libraries used included TensorFlow and Keras for the construction of the Deep Learning architecture, as well as OpenCV for digital image processing. In addition, supporting libraries such as Pandas, NumPy, Matplotlib, and Scikit-learn were used for data manipulation, statistical analysis, and visualization of model evaluation results.

Algorithm Application

Convolutional Neural Network (CNN) is a type of deep learning architecture specifically designed to process visual data and has been proven effective in various visual pattern recognition tasks [11]. After preprocessing is complete, the CNN algorithm is applied to the training data. YOLOv8 and VGG16 are implemented separately to process the prepared data.

1. YOLOv8

   YOLOv8, known as a cutting-edge object detection model, is used to recognize and classify products directly from whole images with fast and accurate detection capabilities [12][13]. This model has demonstrated outstanding performance in various domains, ranging from food logistics to high-precision classification [14]. YOLOv8 uses a single-stage detection mechanism that predicts bounding boxes and class probabilities directly on a single network. Its main formula is written as follows.

$$P_{cls} = \sigma C \times \sigma(O) \quad (1)$$

   with:

   - P_{cls} = predicted class probability for each object
   - σC = classification score,
   - $\sigma(O)$ = objectness score indicating the presence or absense of object in the prediction box

   A visualization of the YOLOv8 method can be seen in **Figure 2**.

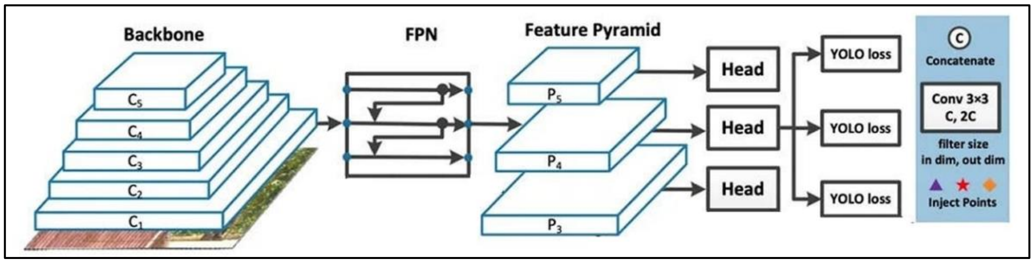

Figure 2. YOLOv8 Visulaization

2. VGG16

VGG16 is used as a conventional image classification model with a deep, layered network architecture, making it suitable for learning visual patterns from images that have been divided into two classes [15], [16]. The VGG16 architecture uses a layered feed-forward approach that extracts features with convolution and then passes them to a fully connected layer. The ReLU activation function is used in each convolutional and dense layer. The general formula is written as follows:

$$f(X) = \max(0, W \cdot X + b) \tag{2}$$

with:

- X = input from the previous layer,
- W = weight (weights),
- b = bias,
- $f(X)$ = ReLU activation output on that layer.

The visualization of the VGG16 method can be seen in **Figure 3**.

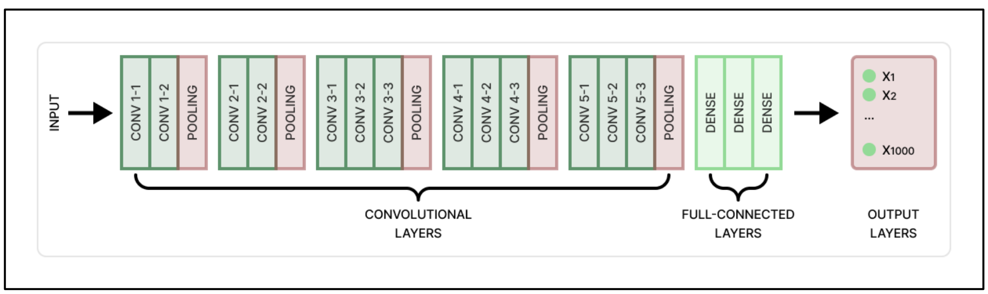

Figure 3. VGG16 Visualization

After the model training process was complete, YOLOv8 and VGG16 were integrated into the developed website-based system. This system allows users to upload product images directly to the platform. The YOLOv8 model will detect objects by drawing bounding boxes and immediately provide product classification results into boycott or non-boycott categories. Meanwhile, the VGG16 model will process images at a resolution of 224x224 pixels and provide class predictions based on the two predetermined categories. The integration of these two models is designed so that users can choose the model to use according to their needs, as well as obtain fast and accurate detection results.

3. Training Hyperparameter

To ensure validity and replication, both models were trained using uniform parameters as listed in **Table 2**.

Table 2. Hyperparameter Configuration

Model	Epoch	Batch Size	Optimizer	Learning Rate
YOLOv8	100	32	SGD	0.01
VGG16	100	32	Adam	0.0001

4. Metric Evaluation

Evaluation is the stage of measuring model performance after training, which aims to determine how well the model generates predictions that match previously unseen data. Accuracy measures how well the model classifies data as a whole, both positive and negative [17]. The evaluation process is carried out after the model has completed the training process. These four metrics (Accuracy, Precision, Recall, F1-Score) are important for evaluating model performance in standard classification tasks [18], [19]. At this stage, evaluation metrics are used to measure the performance of each model against the test data. The results then form the basis for comparing the effectiveness of the two models in detecting boycott products based on image input.

Accuracy measures how accurately the model classifies the data as a whole, both positive and negative [20]. Precision assesses the accuracy of the model in predicting positive classes [21]. while recall shows how well the model finds all the actual positive data. The F1-score is used to balance precision and recall, especially when the data distribution is imbalanced [22]. These four metrics are important for evaluating model performance in classification tasks. The metric equations are shown in equations (3-6).

$$Accuraccy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{3}$$

$$Precison = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

3. Result and Discussion

Testing was conducted on two Convolutional Neural Network architectures, namely YOLOv8 and VGG16, using the dataset as test data. Each model was used to classify product images into boycott and non-boycott categories through a website-based system that had been developed. The test results from both models are shown in **Figure 4** and **Figure 5**.

Figure 4. YOLOv8 model testing results

Figure 5. VGG16 model testing results

YOLOv8 shows excellent performance, characterized by high accuracy and near-perfect precision. This model is capable of detecting boycott products without positive classification errors, while VGG16 provides lower results, especially in the recall metric, although its precision is still quite high. These findings are in line with the research by Wang et al. (2021) and Khow et al. (2024), which confirms that modern object detection architectures are superior to traditional CNN classifiers for product recognition tasks in real-world environments [8], [23]. The advantage of YOLOv8 lies in its ability to separate objects from complex backgrounds, a major challenge in retail product recognition [24], [25]. This shows that VGG16 tends to be more conservative in determining whether a product belongs to the boycott category. The evaluation results of YOLOv8 and VGG16 are shown in **Table 3** below.

Table 3. Evaluation of YOLOv8 and VGG16

Model	Metode Evaluasi	Jumlah
YOLOv8	True Positive	316
	True Negative	74
	False Positive	1
	False Negative	34
	Accuracy	0.917
	Precision	0.997
	Recall	0.903
	F1-score	0.949
VGG16	True Positive	203
	True Negative	15
	False Positive	46
	False Negative	161
	Accuracy	0.513
	Precision	0.816
	Recall	0.557
	F1-score	0.662

Based on the evaluation results in the YOLOv8 and VGG16 tables above, it can be seen that the two models have different performances in detecting boycott and non-boycott products. YOLOv8 shows more stable and consistent results on all evaluation metrics compared to VGG16, which has greater variation, especially on the recall metric. YOLOv8 performs very well in detecting boycott products. This model recorded an accuracy of 91.7%, with a precision of 99.7%, a recall of 90.3%, and an F1-score of 94.9%. The near-perfect precision indicates that most boycott product predictions are correct, with no errors in classifying non-boycott products as boycott products. The high F1-score also indicates a strong balance between accuracy and completeness of detection.

In contrast, the VGG16 model shows much lower results. This model's accuracy only reaches 51.3%, with a precision of 81.6%, a recall of 55.7%, and an F1-score of 66.2%. Although its precision value is still quite good, the low recall value indicates that many boycott products are not recognized. This means that this model often misses objects that should be classified as boycott, making it less than ideal for standalone application in real systems.

The main advantage of YOLOv8 lies in its ability to perform direct object detection in a single stage, making the classification process fast and efficient. This model is also more flexible in recognizing objects from various angles, lighting conditions, and backgrounds, which is highly relevant to real-world product images. Error analysis shows that VGG16 often fails to detect products when the image background is too cluttered or the lighting is poor. In contrast, one False Positive error in YOLOv8 was caused by the similarity between non-boycotted product packaging and the target product. Based on these findings, it is clear that the choice of model architecture has a major influence on the success of the system. YOLOv8 proved to be more suitable for use in web-based real-time detection systems, while VGG16 was more limited in its ability to handle complex object classification, such as various product shapes and packaging. This failure of VGG16 is consistent with the findings of Adegun et al. (2023) in the context of object detection in complex images [26], and demonstrates the limitations of VGG16 transfer learning on datasets with large scale variations [27], [28].

The system developed in this study has real potential in helping the public quickly and accurately identify boycott products. Thus, this system can become a digital tool that supports technology-based social movements.

However, there are several limitations to this study. The dataset used is still limited to 4,250 images, and the system relies solely on visual images without considering additional information such as brand text or logos. For further development, integration with technologies such as OCR (Optical Character Recognition) or Natural Language Processing can help the system recognize a broader context of products. In addition, testing the system by directly involving users in a real environment is also important. Evaluation from the user experience perspective will provide a more accurate picture of the effectiveness and convenience of the system when used in everyday situations.

4. Conclusion

The website-based boycott product detection system that we created using the Convolutional Neural Network (CNN) method with two architectures, YOLOv8 and VGG16, is capable of accurately detecting boycotted and non-boycotted food and beverage products. The results of our tests using the YOLOv8 architecture yielded an accuracy value of 91.7%, precision of 100%, recall of 90.3%, and an f1-score of 94.9%, while the VGG16 architecture yielded an accuracy value of 51.3%, precision of 81.6%, recall of 55.7%, and an f1-score of 94.9%. and an F1-score of 66.2%. The model's ability to be adapted to similar cases, such as waste or plant disease detection, demonstrates the flexibility of this architecture [29]. For further development, it is recommended to combine visual and textual features to improve accuracy on similar packaging [30]. This research is expected to be a starting point for the development of intelligent systems that contribute to social interests through artificial intelligence-based technology, with a focus on increasing dataset variety, developing real-time features, expanding product categories, improving user interfaces, and automatically updating datasets and models to make the system more responsive and relevant.

Although this system has proven to be functional, this study has limitations because the dataset only covers food and beverage categories from a single data source, and relies entirely on visual features without explicitly modeling text cues or logos. Furthermore, this study has not measured computational efficiency (inference time) in depth. For further development, it is recommended to integrate Optical Character Recognition (OCR) to read brand labels, apply domain adaptation techniques to recognize previously unseen packaging, and test the system in real-world environments to validate the model's robustness against complex lighting conditions.

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